On-Line Domain Knowledge Management for Case-Based Medical Recommendation

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Abstract. Domain knowledge may be used in a medical application to avoid wrong decisions, e.g., decisions raising contraindications. The contribution of this paper is twofold. First, it presents an approach for exploiting domain knowledge in a case-based decision support system in the domain of oncology. This approach is based on the so-called conservative adaptation that provides a solution necessarily consistent with the domain knowledge. Second, this paper describes an approach for the evolution of this domain knowledge when the expert rejects a proposed solution as being inconsistent with his/her knowledge. This inconsistency is characteristic of a difference between the domain knowledge of the system and the expert knowledge; from an interactive analysis, a piece of knowledge to be added to the domain knowledge is pointed out. This approach to domain knowledge evolution is implemented in a prototype called FRAKAS.

1 Introduction

One of the key issues for the development of a case-based decision support system in a medical domain is to make its user avoid wrong decisions, since they may have disastrous consequences. Therefore, warnings can be used to assure the user is keeping a critical eye on the proposed solution (i.e., this amounts to issues on ergonomics of man-machine interfaces). This can also be done by associating explanations to the proposed solution [1]. Finally, some wrong decisions may be avoided thanks to the domain knowledge DK (also known as domain ontology). For example, if it is stated in DK that a treatment is contraindicated for a class of patients and if the target patient belongs to this class, then this treatment must not be recommended to the patient.

Hence, domain knowledge may be used to control the CBR inference and to make it avoid some wrong decisions. This knowledge has to be managed, meaning that it must be *capitalized*, *exploited* (by reasoning processes), *shared*, and that it must *evolve*. This paper concentrates on the second and fourth issues of this management: the exploitation and the evolution of domain knowledge for a CBR medical application.

Section 2 presents the KASIMIR project which aims at decision knowledge management in oncology. This research project motivates the exploitation and the evolution of domain knowledge. Its exploitation is performed by CBR processes and this paper

concentrates on a novel approach to it, *conservative adaptation*, that is described in section 3. This approach provides a solution (a recommendation) that is consistent with DK but may be inconsistent with the expert knowledge, due to the gap between DK and this knowledge. Such a failure can be analyzed interactively with the expert and leads to a new (repaired) solution together with a new piece of knowledge that is added to DK. This constitutes an evolution of the domain, as detailed in section 4. Section 5 discusses application of this work to case-based medical recommendation. Section 6 concludes this paper and highlights some future work.

2 The 3 stages of the KASIMIR project

Medical context. The KASIMIR project aims at decision knowledge management in oncology in the framework of Lorraine, a region of France. In this region, decision making in oncology is based on *protocols* and *therapeutic decision meetings* (TDMs).

A *protocol* is a document describing the standard way of decision making in a particular medical domain. For example, the breast cancer treatment protocol (simply called "the protocol" in the following of the paper) explains the standard treatment for the patients suffering from breast cancer. The protocol can be seen as a set of rules $\texttt{Pat} \longrightarrow \texttt{Ttt}$ where Pat is the representation of a class of patients by conditions on their features and Ttt is the treatment recommendation for these patients. Unfortunately, it is not possible in practice to enumerate all the possible conditions that make a treatment applicable and desirable: there are a lot of exceptions in the real world. This is an instance of what John McCarthy calls the qualification problem [2]. In practice, the straight application of the protocol only gives a satisfying therapeutic recommendation in 60 to 70% of the medical cases, according to the experts involved in the KASIMIR project and to their everyday medical practice.

The other cases –called *out of the protocol cases* in the following– are examined during TDMs that gather experts in each of the specialties involved in breast cancer treatment (chemotherapy, radiotherapy, surgery, etc.). It has been shown that during TDMs, the protocol is frequently used to solve the out of protocol cases, but is not straightforwardly applicated: it is *adapted* to the peculiar features of the out of protocol cases [3].

A side-effect of the TDMs is that, through discussions between experts during these problem-solving sessions, the knowledge of these experts evolves.

In summary, decision making in oncology is based on (1) application and on (2) adaptation of the protocol and may lead to (3) an evolution of the expert knowledge.

The KASIMIR project. The KASIMIR project is also based on this 3 stage structure. The protocol is represented in a knowledge representation formalism (namely, the expressive description logic OWL DL for the last version of the KASIMIR system) and protocol adaptation is performed by a deductive reasoning mechanism based on this formalism.

Protocol adaptation is considered as being a CBR process. More precisely, each rule $\texttt{Pat} \longrightarrow \texttt{Ttt}$ is considered as a source case $(\texttt{srce}, \texttt{Sol}(\texttt{srce}))$ –srce is a source problem and $\texttt{Sol}(\texttt{srce})$ is a solution of srce– and thus the protocol *is* the set of source

cases, i.e., the case base. A target problem $\texttt{tgt}$ represents an out of the protocol patient and protocol adaptation consists in (a) selecting a protocol rule $(\texttt{Pat} \longrightarrow \texttt{Ttt}) = (\texttt{srce}, \texttt{Sol}(\texttt{srce}))$ such that $\texttt{srce} = \texttt{Pat}$ is judged to be similar to $\texttt{tgt}$ and (b) modifying $\texttt{Sol}(\texttt{srce}) = \texttt{Ttt}$ to the context of the target problem. Thus, protocol adaptation is a CBR process where (a) is the retrieval step of this process and (b) is its adaptation step. The research on protocol adaptation is synthesized in [4] but the present paper describes another approach, based on the so-called *conservative adaptation* (cf. section 3). It must be noticed that a feature of this approach to case adaptation is that it provides a solution $\texttt{Sol}(\texttt{tgt})$ to $\texttt{tgt}$ that is necessarily consistent with the domain knowledge $\texttt{DK}$.

The third stage of the KASIMIR project is the knowledge evolution. This paper presents an approach based on an interactive failure analysis. More precisely, the failure that is considered in this paper corresponds to an inconsistency of the solution $\texttt{Sol}(\texttt{tgt})$ with the expert knowledge, which points out a difference between this knowledge and $\texttt{DK}$. Therefore, an analysis of this failure leads to an evolution of $\texttt{DK}$ that makes it closer to the domain knowledge. This interactive domain knowledge evolution is described in section 4.

3 Applying Conservative Adaptation to Medical Recommendations

The principle of conservative adaptation is to keep as much as possible from the source case while being consistent with the target problem and the domain knowledge. This approach to adaptation can be formalized thanks to a revision operator $\circ$: given two knowledge bases ψ and μ, $\psi \circ \mu$ is a knowledge base that entails μ and keeps as much as possible from ψ. The AGM theory of revision (called after the [5]'s author initials) consists in a set of postulates that a revision operator has to verify. This theory has been applied to propositional logic (see [6]), and this is in this formalism that the conservative adaptation has been formalized in [7]. In the present paper, the general ideas of this approach to adaptation and an example of a conservative adaptation of a breast cancer treatment is proposed.

Preliminaries. Let $\mathcal{V}$ be a finite set of propositional variables and $\mathcal{V}_{\texttt{pb}}$ and $\mathcal{V}_{\texttt{sol}}$ be two disjoint subsets of $\mathcal{V}$. A *problem* $\texttt{pb}$ (resp., a *solution* $\texttt{Sol}(\texttt{pb})$) is defined as being a propositional formula on $\mathcal{V}_{\texttt{pb}}$ (resp., on $\mathcal{V}_{\texttt{sol}}$). A *case* $(\texttt{pb}, \texttt{Sol}(\texttt{pb}))$ can thus be represented by the formula $\texttt{pb} \wedge \texttt{Sol}(\texttt{pb})$. $\texttt{DK}$ is a formula on $\mathcal{V}$ representing the domain knowledge. An interpretation $\mathcal{I}$ is a function from $\mathcal{V}$ to the pair $\{\texttt{true}, \texttt{false}\}$. If $a \in \mathcal{V}$, $\mathcal{I}(a)$ is also denoted by $a^{\mathcal{I}}$. $\mathcal{I}$ is extended on the set of formulas in the usual way ($(f \wedge g)^{\mathcal{I}} = \texttt{true}$ iff $f^{\mathcal{I}} = \texttt{true}$ *and* $g^{\mathcal{I}} = \texttt{true}$, etc.). A model of a formula f is an interpretation $\mathcal{I}$ such that $f^{\mathcal{I}} = \texttt{true}$. $\texttt{Mod}(f)$ denotes the set of models of f. f is satisfiable means that $\texttt{Mod}(f) \neq \emptyset$. f entails g (resp., f is equivalent to g), denoted by $f \models g$ (resp., $f \equiv g$), if $\texttt{Mod}(f) \subseteq \texttt{Mod}(g)$ (resp., $\texttt{Mod}(f) = \texttt{Mod}(g)$), for two formulas f and g. Finally, $g \models_f h$ (resp., $g \equiv_f h$) means that g entails h (resp., g is equivalent to h) under f: $f \wedge g \models h$ (resp., $f \wedge g \equiv f \wedge h$).

The postulates for a revision operator $\circ$ in propositional logic can be found in [6]. Here, besides the intuition presented above, only two of the six postulates are pointed out:

(R1) $\psi \circ \mu \vDash \mu$ (the revision operator has to retain all the knowledge of the new knowledge base μ);
(R2) If $\psi \wedge \mu$ is satisfiable, then $\psi \circ \mu \equiv \psi \wedge \mu$ (if the new knowledge base does not contradict the old one, then every piece of knowledge of the two bases has to be kept).

The revision operator of Dalal [8], $\circ_{\mathrm{D}}$, can be defined as follows. Let $\mathtt{dist}$ be the Hamming distance between interpretations: $\mathtt{dist}(\mathcal{I}, \mathcal{J})$ is the number of $a \in \mathcal{V}$ such that $a^{\mathcal{I}} \neq a^{\mathcal{J}}$. Given two sets of interpretations M_1 and M_2, and an interpretation $\mathcal{J}$, $\mathtt{dist}(M_1, \mathcal{J})$ is the minimum of $\mathtt{dist}(\mathcal{I}, \mathcal{J})$ for $\mathcal{I} \in M_1$ and $\mathtt{dist}(M_1, M_2)$ is the minimum of $\mathtt{dist}(M_1, \mathcal{J})$ for $\mathcal{J} \in M_2$. Now, for $\lambda \geq 0$ and a formula ψ, let $G^{\lambda}(\psi)$ be a formula such that:

$$\mathtt{Mod}(G^{\delta}(\psi)) = \{\mathcal{J} \mid \mathcal{J}\text{: interpretation on } \mathcal{V} \text{ and } \mathtt{dist}(\mathtt{Mod}(\psi), \mathcal{J}) \leq \delta\}$$

(this defines G^{λ} up to the logical equivalence $\equiv$). The formulas $G^{\lambda}(\psi)$ realizes a generalization scale of ψ, in the sense that $\psi \equiv G^0(\psi) \vDash G^{\lambda}(\psi) \vDash G^{\varepsilon}(\psi)$ for any λ and ε such that $0 \leq \lambda \leq \varepsilon$. Intuitively, the revision of ψ by μ according to the Dalal revision operator consists in generalizing in a minimal way ψ (along this scale) to make it consistent with μ. More precisely, if Δ is the minimal value such that $G^{\Delta}(\psi) \wedge \mu$ is consistent, then $\psi \circ_{\mathrm{D}} \mu = G^{\Delta}(\psi) \wedge \mu$ (such a Δ exists; in fact: $\Delta = \mathtt{dist}(\mathtt{Mod}(\psi), \mathtt{Mod}(\mu))$).

Formalization of conservative adaptation. Let $\mathtt{tgt}$ be a problem and $\mathtt{srce} \wedge \mathtt{Sol}(\mathtt{srce})$ be a case. The adaptation of this case to solve $\mathtt{tgt}$ aims at giving a solution $\mathtt{Sol}(\mathtt{tgt})$ of $\mathtt{tgt}$. Given a revision operator $\circ$, the $\circ$-conservative adaptation consists in computing

$$\mathtt{CA}_{\circ}(\mathtt{DK}, \mathtt{srce} \wedge \mathtt{Sol}(\mathtt{srce}), \mathtt{tgt}) = (\mathtt{DK} \wedge \mathtt{srce} \wedge \mathtt{Sol}(\mathtt{srce})) \circ (\mathtt{DK} \wedge \mathtt{tgt})$$

The result of this computation is a formula f such that $f \equiv_{\mathtt{DK}} \mathtt{tgt} \wedge \mathtt{Sol}(\mathtt{tgt})$ which gives a solution $\mathtt{Sol}(\mathtt{tgt})$ to $\mathtt{tgt}$.

This definition formalizes the idea that conservative adaptation consists in keeping as much as possible from $\psi = \mathtt{DK} \wedge \mathtt{srce} \wedge \mathtt{Sol}(\mathtt{srce})$, i.e., the source case interpreted in the framework of the domain knowledge, while being consistent with $\mu = \mathtt{DK} \wedge \mathtt{tgt}$, i.e., the target problem interpreted in the framework of $\mathtt{DK}$.

Example. Let us consider the example of a patient who is a woman with positive hormone receptors (*HR+*), who has already had a radical mastectomy with a lymph node dissection (*Patey-done*: Patey is the name of this surgery act), with no involved lymph nodes (*N-*), who has a liver disease (*liver-disease*) and some other characteristics not detailed here (γ, that compiles pieces of information about her gender, her age, her tumor size, etc.). This patient corresponds to the following problem:

$$\mathtt{tgt} = \textit{HR+} \wedge \textit{Patey-done} \wedge \textit{N-} \wedge \textit{liver-disease} \wedge \gamma$$

Now, let us consider the source case $\texttt{srce} \wedge \texttt{Sol}(\texttt{srce})$ such that

$$\texttt{srce} = \textit{HR+} \wedge \textit{Patey-done} \wedge \textit{N-} \wedge c$$
$$\texttt{Sol}(\texttt{srce}) = \textit{FEC} \wedge \textit{tamoxifen}$$

In other words, this case corresponds to the protocol rule "If the patient has positive hormone receptors, has already had a Patey surgery, no involved lymph nodes, and some other characteristics not detailed here (denoted by c), then a treatment composed of a chemotherapy based on FEC and a hormone therapy based on tamoxifen is recommended." Tamoxifen is a hormone therapy drug and FEC is composed of three chemotherapy drugs: fluorouracil, epirubicin, and cyclophosphamide.

Now, let us consider the following domain knowledge:

$$\begin{aligned}
\texttt{DK} = {} & \gamma \Rightarrow c && (1)\\
& \wedge \textit{liver-disease} \Rightarrow \neg \textit{tamoxifen} && (2)\\
& \wedge (\textit{tamoxifen} \vee \textit{anti-aromatases} \vee \textit{ovary-ablation}) \Leftrightarrow \textit{anti-oestrogen} && (3)\\
& \wedge \textit{FEC} \Leftrightarrow (\textit{fluorouracil} \wedge \textit{epirubicin} \wedge \textit{cyclophosphamide}) && (4)
\end{aligned}$$

(1) indicates that a patient having the characteristics represented by γ has the characteristics represented by c. (2) indicates that tamoxifen is contraindicated for persons having a liver disease. (3) indicates that tamoxifen, anti-aromatases, and ovary ablation are anti-oestrogen treatments and that they are the only available anti-oestrogen treatments (in the context of a given hospital). Finally, (4) indicates how a FEC treatment is composed: it indicates that a FEC treatment is recommended iff fluorouracil, epirubicin, and cyclophosphamide are recommended.

Since tgt corresponds to a specific situation of the general case srce ($\texttt{tgt} \models_{\texttt{DK}} \texttt{srce}$), the source case $(\texttt{srce}, \texttt{Sol}(\texttt{srce}))$ is selected by the retrieval process. However, a straightforward application of this source case contradicts the target problem, given the domain knowledge: $\texttt{DK} \wedge \texttt{srce} \wedge \texttt{Sol}(\texttt{srce}) \wedge \texttt{tgt}$ is unsatisfiable (since $\texttt{DK} \wedge \textit{liver-disease} \wedge \textit{tamoxifen}$ is). The $\circ_{\text{D}}$-conservative adaptation gives:

$$\begin{aligned}
& \texttt{CA}_{\circ_{\text{D}}}(\texttt{DK}, \texttt{srce} \wedge \texttt{Sol}(\texttt{srce}), \texttt{tgt})\\
& \equiv_{\texttt{DK}} \texttt{tgt} \wedge \underbrace{\textit{FEC} \wedge (\neg \textit{tamoxifen} \wedge (\textit{anti-aromatases} \vee \textit{ovary-ablation}))}_{\texttt{Sol}(\texttt{tgt})}
\end{aligned}$$

Tamoxifen, since it is contraindicated for the target patient, is removed, but according to the conservative adaptation principle, as much as possible from $\texttt{Sol}(\texttt{srce})$ is kept. In particular, $\textit{tamoxifen} \models_{\texttt{DK}} \textit{anti-oestrogen}$ and *anti-oestrogen* is kept ($\texttt{tgt} \wedge \textit{anti-oestrogen}$ is consistent). Thus, $\textit{anti-aromatases} \vee \textit{ovary-ablation}$ is proposed, following (3): $\neg \textit{tamoxifen} \wedge \textit{anti-oestrogen} \models_{(3)} \textit{anti-aromatases} \vee \textit{ovary-ablation}$. Therefore, the hormone therapy recommended for the target patient according to $\texttt{Sol}(\texttt{tgt})$, is a cure of anti-aromatases or an ovary ablation.

Remark. Conservative adaptation may also be seen as an instanciation of the reuse and revise steps of the Aamodt and Plaza's cycle [9]: reuse is performed by a simple

copy and revise by a revision operator. It can be noticed that, to our knowledge, the revise step of the CBR cycle has not been related to the AGM theory of revision: we have found only two papers on CBR using revision techniques. The first one is [10], where revision was not used for the purpose of the reasoning process itself, but for the maintenance of the case base and of a rule base when there are some evolutions in time. The second one is [11][1] where a conservative plan modification strategy is defined and related to revision. It appears that this strategy may be more complex (from an algorithmic viewpoint) compared to non-conservative plan modification strategy. In our approach, CBR is not used as a heuristic to speed up a first principle reasoner. Nevertheless, a more careful comparison with [11] has to be carried out.

4 Failure Analysis for Medical Knowledge Acquisition

FRAKAS (FailuRe Analysis for domain Knowledge AcquiSition) is a prototype developed to illustrate the principles of domain knowledge acquisition based on adaptation failure analysis. In this prototype, the source case $\texttt{srce} \wedge \texttt{Sol}(\texttt{srce})$ is adapted by performing a conservative adaptation to solve the target problem tgt. The proposed solution is presented to the expert who analyzes it and detects possible failures, thanks to a graphical interface. Currently, two kinds of failures are handled by FRAKAS: (1) the adapted solution is inconsistent with the expert knowledge and (2) the solution is partial and the expert must make it precise before applying it.

In this section, we describe how FRAKAS processes the example introduced above. We focus on the first kind of failure, i.e., when the solution proposed by the system is inconsistent with the expert knowledge. More details about FRAKAS and the two kinds of failures can be found in [12].

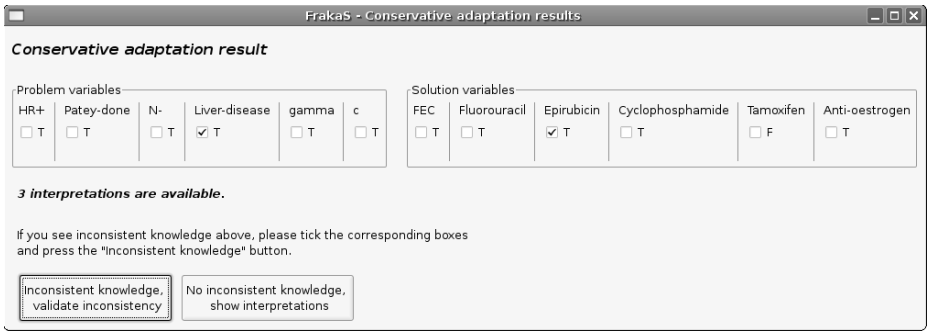
Study of the example with FRAKAS. In this example, the source case $\texttt{srce} \wedge \texttt{Sol}(\texttt{srce})$ introduced above is adapted to solve tgt. The conservative adaptation produces a set of interpretations (FRAKAS uses propositional logic as knowledge representation formalism). Each interpretation is a possible solution of tgt.

To present a solution to the expert, FRAKAS proceeds in two steps: firstly only the variables interpreted in the same way by all the interpretations are shown and then, if this first part of the solution is validated by the expert, all the available interpretations are displayed. Figure 1(a) shows the result of the conservative adaptation performed according to DK and the feedback of the expert in form of checked boxes. It can be observed that the expert indicates an inconsistency between the proposed solution and his/her knowledge: *epirubicin* is inconsistent with *liver-disease*. The system uses this feedback to acquire a new piece of knowledge. In figure 1(b), the confirmation screen is presented: the acquired piece of knowledge is expressed in propositional logic and the expert can add a textual explanation before allowing the system to learn this knowledge. Textual explanations may be used off-line to acquire more domain knowledge.

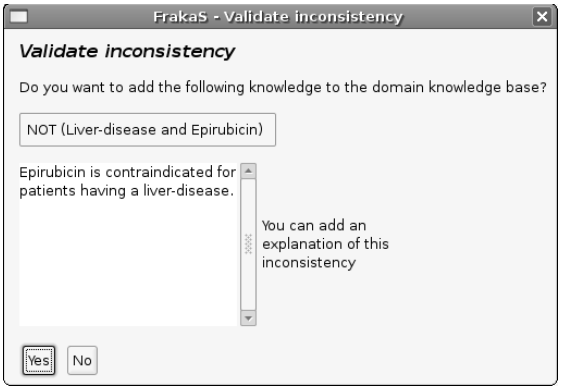
Thus, after this step, the domain knowledge DK has evolved into $\texttt{DK}'$:

$$\texttt{DK}' = \texttt{DK} \wedge \neg(\textit{liver-disease} \wedge \textit{epirubicin}) \equiv \texttt{DK} \wedge (\textit{liver-disease} \Rightarrow \neg \textit{epirubicin})$$

[1] Many thanks to the anonymous referee who has suggested this reference.



(a) Result of the first conservative adaptation and feedback of the expert in form of checked boxes: the expert points out an inconsistency between the domain knowledge and his/her knowledge.



(b) The expert provides an explanation in plain text.

Fig. 1. First solution presented to the expert and his/her feedback (a). Plain text explanation provided by the expert (b).

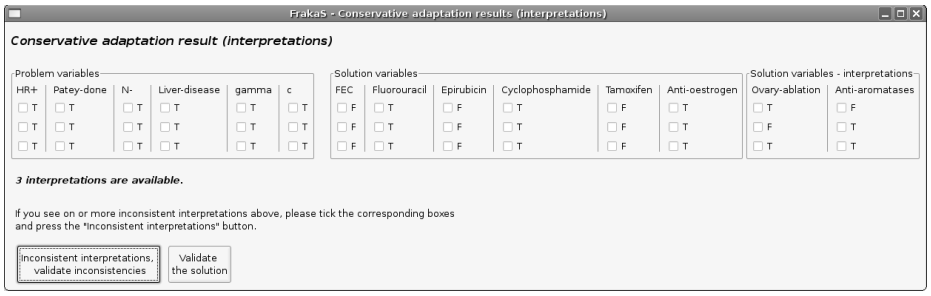


Fig. 2. Solution presented to the expert, who validates it.

Then, a new conservative adaptation is performed with $\mathtt{DK}'$:

$$\mathtt{CA}_{\circ_D}(\mathtt{DK}', \mathtt{srce} \wedge \mathtt{Sol}(\mathtt{srce}), \mathtt{tgt})$$
$$\equiv_{\mathtt{DK}'} \mathtt{tgt} \wedge \left(\begin{array}{c} \neg \textit{FEC} \wedge \neg \textit{epirubicin} \wedge \textit{fluorouracil} \wedge \textit{cyclophosphamide} \\ \wedge\ \textit{anti-oestrogen} \wedge \neg \textit{tamoxifen} \wedge (\textit{anti-aromatases} \vee \textit{ovary-ablation}) \end{array} \right)$$

Since they are both inconsistent with $\mathtt{DK}' \wedge \mathtt{tgt}$, the system does not keep *epirubicin* and *FEC* in the new solution. As the expert validates the first part of the solution (common variables), the system displays the three possible interpretations (cf. figure 2). Since each interpretation is correct, the expert validates the solution.

5 Discussion

In [13], some adaptation patterns for case-based decision support are presented, that were elaborated during sessions of adaptation knowledge acquisition from experts in oncology, on the basis of actual medical cases. These patterns are generally based on the following features of a decision: its applicability, its positive consequences (i.e., its expected therapeutic benefits), and its negative consequences (i.e., its undesirable effects). This section shows how some of the adaptations matching these patterns may be modeled by a case-based decision process that provides a solution consistent with the domain knowledge (such as a process with a conservative adaptation): they correspond to some pieces of knowledge f either in DK or that can be acquired by failure analysis.

The fact that a treatment ttt is *inapplicable* for a class of patients pat can be modeled by the piece of knowledge $f = \mathtt{pat} \Rightarrow \neg\mathtt{ttt}$. Thus, if $\mathtt{Sol}(\mathtt{srce}) \models_{\mathtt{DK}} \mathtt{ttt}$, $\mathtt{tgt} \models_{\mathtt{DK}} \mathtt{pat}$, $\mathtt{DK} \models f$, and if $\mathtt{Sol}(\mathtt{tgt})$ is consistent with $\mathtt{DK} \wedge \mathtt{tgt}$, then $\mathtt{Sol}(\mathtt{tgt}) \not\models_{\mathtt{DK}} \mathtt{ttt}$. For example, an ovary ablation cannot be performed on a man (for obvious reasons): $f = \textit{man} \Rightarrow \neg\textit{ovary-ablation}$.

The fact that a treatment ttt is *contraindicated* for a class of patients pat means that its negative consequences are too high. It can be modeled in the same way as for inapplicable treatments: $f = \mathtt{pat} \Rightarrow \neg\mathtt{ttt}$. Two examples of contraindications have been presented in the two previous sections: they correspond to $f = \textit{liver-disease} \Rightarrow \neg\textit{tamoxifen}$ and to $f = \textit{liver-disease} \Rightarrow \neg\textit{epirubicin}$.

The fact that a treatment ttt is *ineffective* for a class of patients pat can be modeled by $f = (\mathtt{ttt} \wedge \mathtt{pat}) \Rightarrow \textit{ineffective-treatment}$. The assumption "An ineffective treatment must be avoided" can be modeled by the piece of knowledge $g = \neg\textit{ineffective-treatment}$. Thus, if $\mathtt{Sol}(\mathtt{srce}) \models_{\mathtt{DK}} \mathtt{ttt}$, $\mathtt{tgt} \models_{\mathtt{DK}} \mathtt{pat}$, $\mathtt{DK} \models f \wedge g$, and if $\mathtt{Sol}(\mathtt{tgt})$ is consistent with $\mathtt{DK} \wedge \mathtt{tgt}$, then $\mathtt{Sol}(\mathtt{tgt}) \not\models_{\mathtt{DK}} \mathtt{ttt}$. For example, tamoxifen is not effective for women with negative hormone receptors ($\neg$*HR+*): $f = (\textit{tamoxifen} \wedge \neg\textit{HR+}) \Rightarrow \textit{ineffective-treatment}$. Therefore, under the assumption $f \wedge g$, if $\mathtt{Sol}(\mathtt{srce})$ is a therapeutic recommendation including tamoxifen, then the recommendation $\mathtt{Sol}(\mathtt{tgt})$ does not include this drug.

6 Conclusion and Future Work

In this paper, one of the key roles of the domain knowledge DK of a case-based decision support system is highlighted: it enables this system to avoid proposing some

wrong solutions (the ones that contradict DK). This is useful in particular for medical applications for avoiding inapplicable, contraindicated, and useless treatment recommendations. This requires an approach to case-based reasoning that provides solutions that are consistent with DK. This is the case for a system using conservative adaptation, an approach to adaptation based on a revision operator and that consists in keeping as much as possible from the source case while being consistent with DK and the target problem (more details can be found in [7]). Unfortunately, due to the qualification problem, there is a gap between DK and the expert knowledge. Thus, a solution consistent with DK may be considered to be inconsistent with the expert. This failure can be analyzed interactively and leads to a new piece of knowledge to be added to DK: this is what the prototype FRAKAS does (see [12] for more details).

This paper is a contribution to formalization of CBR in health science, a trend presented in [14]. Indeed, it proposes a formalization of reasoning from medical cases with the help of the domain knowledge. Furthermore, it is destinated to be integrated in the KASIMIR system that is based on semantic Web technologies for representing cases and domain knowledge [15]: the Web ontology language OWL is used as it is in the Mémoire system [16].

The research about conservative adaptation and FRAKAS is still at its beginning and there are several research directions. Some of them are presented in [7] for conservative adaptation and in [12], for FRAKAS. Two other directions of research are more about medical applications, though they may be extended to other domains.

In section 5, binary distinctions between treatment recommendations for a patient are made: applicable/inapplicable, non contraindicated/contraindicated, and useful/useless. In the real world, these distinctions are often gradual. For example, let us consider an aged patient, with low mobility, living far from a radiotherapy center. This situation makes the recommendation of daily radiotherapy sessions during 3 weeks difficult to apply but not strictly inapplicable. In such a situation, the recommendation may be different from a binary choice (either this daily radiotherapy or no radiotherapy): it may be a compromise (such as a radiotherapy with less frequent sessions). How these gradual situations could be handled thanks to conservative adaptation is an open research issue.

Another future work is to improve the modeling of these reasons to adapt (inapplicability, contraindication, uselessness). For example, the contraindication of a treatment ttt for a class of patients pat has been modeled by $\texttt{pat} \Rightarrow \neg\texttt{ttt}$. Now, consider the contraindication of epirubicin for patients with a heart problem. One way to adapt a FEC treatment is by removing epirubicin (as in section 4). Another way is to keep epirubicin and to add a drug that prevents from the undesirable effects of epirubicin on the heart. This solution is sometimes recommended by physicians but is not consistent with $f = \textit{heart-problem} \Rightarrow \neg \textit{epirubicin}$. Therefore, a more sophisticated modeling of contraindications is required, and this may also be true for the modeling of treatment inapplicability and treatment uselessness. This also raises the problem of the FRAKAS interface: with the above example, the expert will probably check the boxes *heart-problem* and *epirubicin*, that leads to the knowledge $\neg(\textit{heart-problem} \wedge \textit{epirubicin})$ which is equivalent to f. In a further version of FRAKAS, a new interface based on the reasons to adapt may be developed. One can imagine such an interface with a tab for each rea-

son to adapt. With the above example, the expert may choose the "contraindication tab" and indicate that *epirubicin* is contraindicated because of *heart-problem*. This involves two improvements with the current version: first, it associates explanations to pieces of knowledge and second, it enables to use a sophisticated model of, e.g., contraindication.

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